# A Closer Look at Remote Sensing

Inaugural address

**Wouter Verhoef**

Professor of Advanced Earth Observation for

Water Resources Applications

7 October 2009

Enschede, The Netherlands

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Dear Mr Rector, members of the Scientific Council, the Supervisory Board, ladies and gentlemen,

As expressed in the mission statement of ITC, the knowledge field of ITC is "*geo-information science and earth observation*, which consists of a combination of tools and methods for the collection (through aerospace survey techniques), storage and processing of geospatial data, for the dissemination and use of these data and of services based on these data".

In geo-information science and earth observation, we are concerned with two important questions (Figure 1):

- Which objects are located where?
- Which physical properties describe an object and what are their values?

The answer to the first question is given by the object's attribute information, and the associated remote sensing data processing operation is called classification or, in more general terms, pattern recognition. The kind of output information produced in this case is of a discrete nature.

The answer to the second question is given by quantitative information on the object's physical properties, and the associated remote sensing data processing operation is usually called parameter retrieval. The kind of output information produced in this case is of a continuous nature. Pixel brightness values in one or more spectral bands are translated into values of one or more surface parameters of interest.

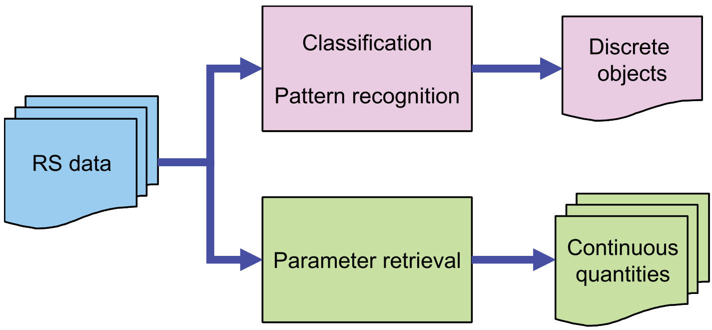


**Figure 1 Use of remote sensing data for classification and parameter retrieval**

On this particular occasion, I will focus on the second question: what quantitative information can be retrieved from optical remote sensing data, covering the spectrum from the visible to the thermal infrared? The answer to this question requires a closer look at the physics behind remote sensing.

Looking back in time, we can state that the technical capabilities of instrumentation on the ground and in aerospace have increased tremendously, as well as the computational power to run models and to process the data. Yet, the retrieval of accurate quantitative information from satellite remote sensing observations still appears to form a challenge. Why is that? The relations between surface properties and observed remote sensing data are quite well known today, so in principle it should be possible to translate remotely sensed data into estimated surface properties. Many so-called radiative transfer models have been developed to describe these relations for water, vegetation and the atmosphere, and in principle these models can also be used in reverse mode to retrieve the properties of interest. The atmosphere must be included here since, for observations of land and water surfaces from space, the observed radiation has to cross the atmosphere - so it must be taken into account.

Retrievable properties are those physical quantities to which the observed radiation is sensitive. In the case of the atmosphere, these include rainfall and cloudiness, water vapour, $CO_2$ and aerosols. For water one can estimate wave height with radar, bottom depth with sonar, water quality with optical instruments, and surface temperature with thermal infrared sensors. For soils one can estimate soil moisture and surface roughness with radar techniques and the soil type with optical sensing. Retrievable vegetation parameters of interest are the leaf area index (LAI), the leaf chlorophyll and water contents, fractional vegetation cover (FVC) and the fraction of absorbed photosynthetically active radiation (fAPAR).

Besides sensitivity, the ability to discriminate between the sensitivities to different parameters is important. This requires linear independence of the responses to the various parameters. Linear independence is more likely with a high number of independent observables. This is the main reason why one can retrieve more information from observations in multiple spectral bands, from multiple viewing angles and at multiple times.

Nevertheless, we can state that, although the physics of earth observation are fairly well understood these days, problems with the correct interpretation of the data are still quite persistent.

This is partly related to the fact that the radiance signal detected on board a satellite is a mixture of components coming from the atmosphere and from the ground. In turn, the ground component is a mixture of vegetation and bare soil or water and the sea bottom. We call this the vertical mixing problem. There is also a horizontal form of mixing. Horizontal mixing has to be considered when pixels are heterogeneous. This form of mixing can be treated as being linear. Vertical mixing is more complicated and non-linear, since higher layers contribute more than lower layers to the signal. Because of these complications, one often has to make simplifying assumptions that are not always justified.

A frequently used assumption is that of a laterally constant atmosphere over the scene, which simplifies the correction for atmospheric effects. However, such ideal conditions are very rare, and actually one should take the spatial variations in atmospheric haze over the scene into account. Particularly over water bodies, a large portion of the measured signal comes from the atmosphere, and one has to apply accurate methods of atmospheric correction. Here, one often makes the assumption of a zero water contribution in the near infrared part of the spectrum, which is often correct but not always. At high sediment concentrations, the water does reflect near infrared radiation, and, if this is wrongly attributed to the atmosphere, the atmospheric effect is overestimated and the sediment contribution underestimated.

As shown in Figure 2, one can apply a coupled water-atmosphere model to unmix atmospheric haze and sediment in the water. This example demonstrates that one should not separate the atmospheric correction step from the subsequent water quality processing step. A better approach is to simultaneously estimate atmospheric and water parameters from a coupled water-atmosphere model, using all available spectral information. In general, focusing too much on a single medium forces one to make assumptions about the other media involved, and this will lead to errors if these assumptions are not valid. Another example: the retrieval of vegetation parameters is influenced by the soil background, yet most retrieval algorithms simply ignore this fact.

A third reason why the interpretation still poses problems is that remote sensing data are often treated as a standalone source of information, ignoring already existing

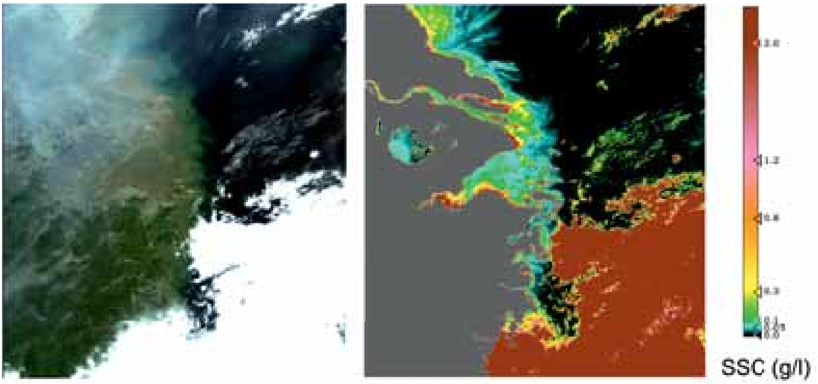


**Figure 2 Haze-sediment unmixing: a natural colour image (MERIS data) of the Yangtze River estuary (Shanghai, China) on the left and the retrieved suspended sediment concentration map on the right**

geographical information. However, existing geographical information on an area can be of great help in correctly interpreting remote sensing data, so this source of information should never be ignored, unless it is known to be of poor quality.

Which earth observation data do we need? More spectral bands mean more information. The same holds for multi-angular and multi-temporal data and for including other types of remote sensing data, such as thermal data and radar data. The spectral, angular and temporal domains can all be exploited to enhance the quality of geographical information. Polarisation and distance measurements (radar and laser altimetry) can be added as extra sources of information. This is called the multi-concept. Multi-sensor approaches can improve the quality of the retrieved information, although it is realised that in practice this may not be easy. In principle, combining many data sources provides more information, but this also leads to more complicated data processing and the need for good visualisation techniques. One example of a visualisation technique is illustrated in Figure 3, in which 36 ten-day images were condensed into a single colour image.

Here, a time series of one year of NDVI data (normalised difference vegetation index, an indicator of green vegetation) was processed into harmonic components, and the mean, the yearly amplitude and the phase were transformed into intensity, saturation and colour hue, respectively. In addition, hill shading was applied by using input from a

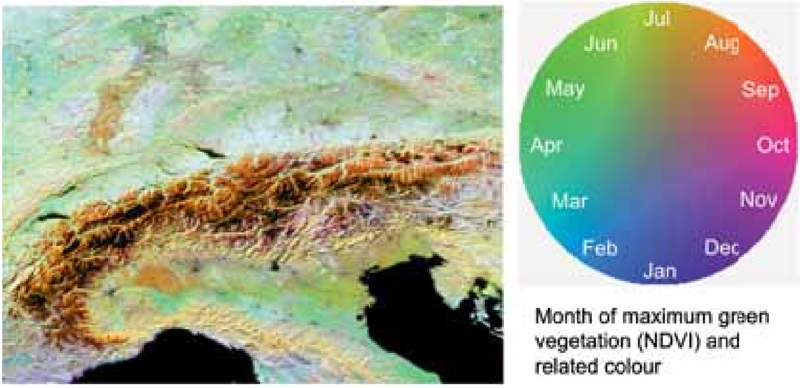


**Figure 3** Visualisation of vegetation growth dynamics and topography for the Alps and surroundings. NDVI yearly mean, amplitude and phase were coupled with pixel intensity, saturation and colour hue, respectively

digital elevation model. In this way, one can view the dynamic behaviour of the vegetation in relation to the local topography. The coloured circle shows the relation between the month of maximum NDVI and the colour hue in the image. One can observe, for instance, that in the Alps the colours go to red-brown and finally become black in the higher regions. In these regions, the vegetation reaches its maximum NDVI in autumn, and in the very high regions, which look black, there is no observable vegetation at all during the whole year, so these are the areas of permanent snow cover. Other colours in this image indicate that the green vegetation reaches its maximum density in spring (green), in summer (yellow) or in winter (blue). The last happens mostly in Mediterranean areas with a dry summer. Finally, grey and white areas indicate a permanent vegetation cover, for instance grasslands or coniferous forests.

The NDVI is an index that is sensitive to the absorption of radiation by green leaves in the red part of the spectrum, as opposed to the near infrared radiation, which is strongly scattered. The normalised difference of near infrared and red is small for bare soils and water, and high for dense green vegetation. A large portion of what we observe in optical remote sensing images is based on the absorption spectra of only a few substances, namely chlorophyll, liquid water and ice. These spectra are shown in Figure 4. Chlorophyll has absorption peaks in the blue and red parts of the spectrum, and a minimum in the green, thus causing the green colour of plants.

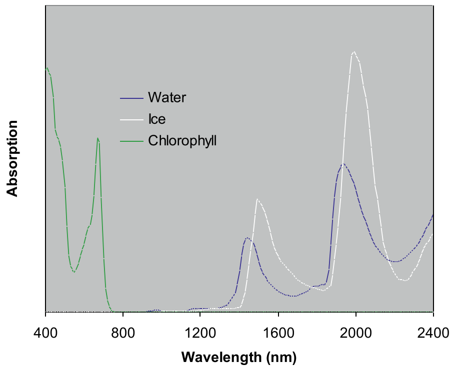


Figure 4 Absorption spectra of chlorophyll, water and ice on arbitrary scales

Water and ice have roughly similar spectra, with high absorption peaks in the shortwave infrared. In the near infrared (750 to 1350 nm), chlorophyll and water absorb little, so in this spectral region plant leaves scatter most radiation. Hence the high values of the NDVI for dense green vegetation.

What do we actually know about the radiation reflected or emitted by objects on Earth and how can we utilise this knowledge for a more quantitative interpretation of satellite images?

Starting with the first, we know quite a lot about the physics of radiative transfer. Not only about the absorption spectra, but also about scattering, which is just as important, and about the relations with optical thickness, an important physical quantity by which concentrations and quantities of materials are measured non-destructively. This knowledge is aggregated in so-called radiative transfer theories. I am deliberately using the plural form here, since there are radiative transfer models for materials such as clouds, aerosols, ocean water, soils, single plant leaves, vegetation canopies, and even snow. Besides, within each category there can be large variations in the levels of accuracy and complexity, and in the applied modelling approaches.

Here I would like to emphasise a couple of features that all of these models have more or less in common. This can be illustrated by means of four simple diagrams (Figure 5), which show the relations between the optical thickness $\tau$ (on a logarithmic scale) on the one hand, and the reflectance (R), the total transmittance (T+U) and the absorptance (A) of a layer of material on the other. Because of the law of energy conservation, the sum of these quantities must always be one, and the diagram shows how the distribution of the radiation changes over these quantities with increasing optical thickness. Optical thickness indicates how much of the material in the layer interacts with the incoming radiation. The white section in each diagram is the portion of the radiation that passes the layer without any interaction, uncollided (U). This direct transmittance is only determined by the optical thickness (and the incidence angle) and must be distinguished from the diffuse transmittance (T), which is caused by forward scattering.

In all cases, the reflectance (and what we observe from space is proportional to it) depends on optical thickness by a kind of S-curve. This means that the relative sensitivity to changes in optical thickness is small for very low as well as for very high optical thickness, and maximum at moderate levels. What can be noticed in the first diagram of Figure 5, in particular, is the wide range of optical thicknesses over which effects can be observed by remote sensing: from about 0.001 to about 1000 - six orders of magnitude! In theory, this opens up tremendous opportunities for estimating the concentrations of substances such as water and chlorophyll.

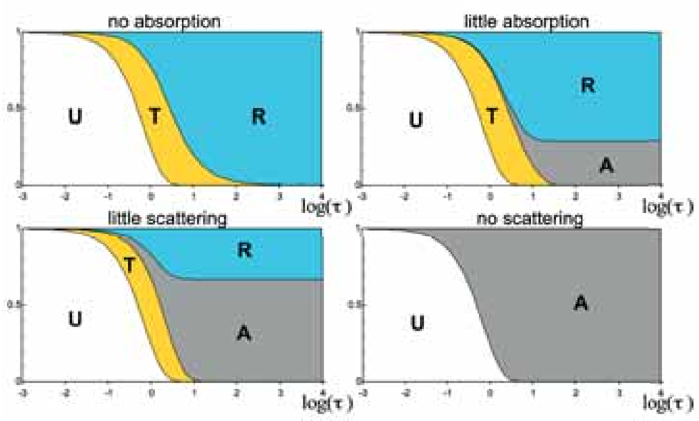


Figure 5 Uncollided (U), diffusely transmitted (T), reflected (R) and absorbed (A) radiation fractions in a layer as a function of its optical thickness (logarithmic scale) in four situations

What differs over the four diagrams is the ratio of absorption to scattering. In the upper left diagram, there is no absorption, only scattering. In this case, we see that the part of the radiation that interacts with the medium produces reflection by upward scattered radiation and diffuse transmission by downward scattered radiation. The part that does not interact with the medium is directly transmitted downward. At very high optical thickness the medium becomes opaque and has no transmittance and a reflectance of one. The case of a low diffuse transmittance and a very high reflectance is representative of thick clouds in the visible part of the spectrum, which are dark at the bottom and very bright at the top. For zero transmittance and a reflectance of one the situation can be compared to that of a thick layer of snow.

In the upper right diagram there is a weak absorption. This results in a largely similar diagram as before, but at high optical thickness we see that the reflectance is much lower, and the absorption in the layer much higher. This situation is representative of many materials on earth, such as turbid water, and vegetation observed in the near infrared.

In the third diagram we have a stronger absorption, and relatively little scattering. This causes a low reflectance and a higher absorption compared to the previous diagram. Many dark materials on Earth represent this situation, such as bare soils, and vegetation in the visible part of the spectrum.

In the fourth diagram there is no scattering, only absorption. A material in which scattering is relatively weak is, for instance, the ocean. This causes the dark appearance of deep clear ocean water in the longer wavelengths (red and near infrared). In the blue parts of the spectrum, scattering still plays a role; hence the blue colour of the sea.

Absorption and scattering are wavelength-dependent. For an optically thick layer, the reflectance depends strongly on the ratio between scattering and absorption. Plotted on a logarithmic scale for this ratio (Figure 6), again an S-shaped curve is obtained - and the range of sensitivity spans about seven orders of magnitude! The highest sensitivity to changes in the scattering and absorption properties of the material occurs at a reflectance level of 0.5, or halfway between the minimum and the maximum reflectance levels. This appears to be a general rule.

Multispectral and hyperspectral remote sensing techniques make intensive use of the variability of the above diagrams with wavelength and with the materials involved.

Particularly the absorption is highly wavelength-dependent, and the absorption spectrum can differ greatly from one material to another. For instance, soils, vegetation, water and the atmosphere all have very distinct absorption characteristics. Figure 7 shows how the absorption spectra of chlorophyll and water shown before in Figure 4 together shape the distribution of reflectance, transmittance and absorption for single plant leaves. In the near infrared, only the dry matter in the leaf absorbs a little radiation, while reflectance and transmittance become about equal.

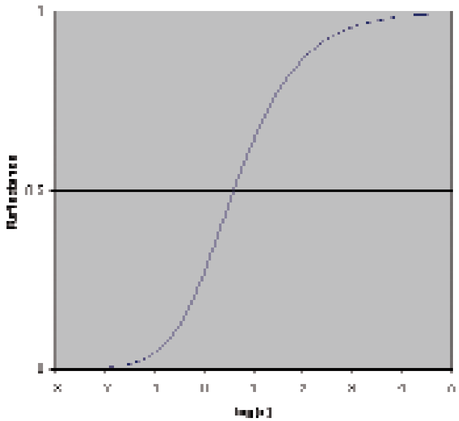

Figure 6  Reflectance as a function of the ratio backscattering / absorption for optically thick media

$$x = \frac{b_h}{a}$$

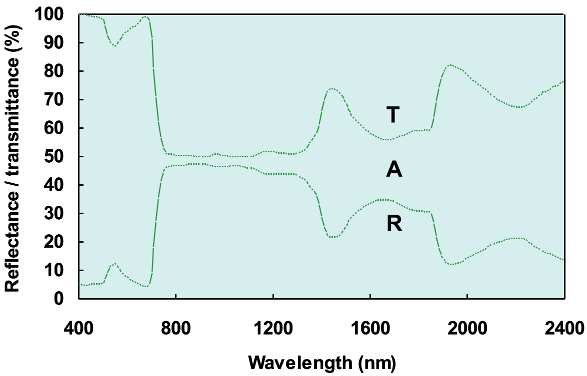


Figure 7  Reflectance (R) and transmittance (T) of a green plant leaf. Transmittance was plotted upside-down from the top. The middle region (A) is the absorptance

The atmosphere has numerous narrow absorption lines, which are caused by oxygen, water vapour, carbon dioxide and many other gases. See Figure 8, which shows the atmospheric transmittance spectrum. In the visible part of the spectrum (400 to 700 nm) there is little absorption, but here scattering by aerosols and air molecules reduces the transmittance of the atmosphere.

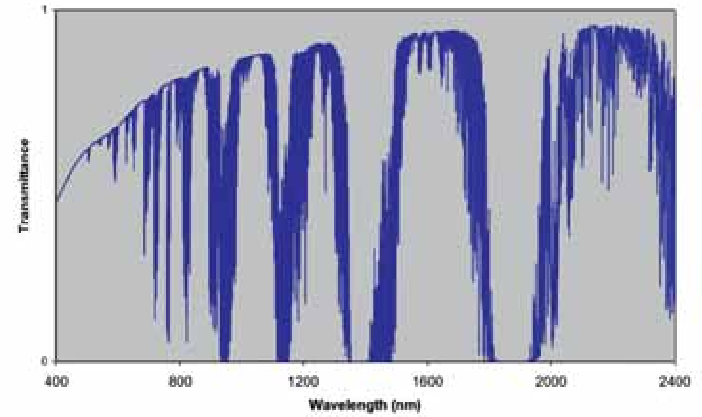


Figure 8  Atmospheric transmittance as a result of scattering and absorption lines

On the Earth's surface, the bottom layer is always opaque, but everything else on top of it (a water body, a vegetation canopy, the atmosphere) can be partly transparent, and this transparency may vary strongly with wavelength. This means that for water bodies we can potentially see through all layers from the top of the atmosphere down to the bottom of the sea, provided we use wavelengths where the transparency is sufficient. This happens to be the case in the visible blue-green part of the spectrum around 500 nm. Here, from space we can even observe spatial variations in the sea bottom (e.g. sandy or vegetated) through the water layer and the atmosphere, provided both are clear enough.

To discriminate between different substances in a mixture and to estimate their relative proportions, it is necessary to use multiple wavelengths. With only one spectral band this is not possible. And if there are more components in the mixture, for instance green leaves, brown leaves, stems and soil, more wavelengths should be used to enable the quantitative retrieval of biophysical properties.

## Observation models and process models

In order to study the relations between object properties and observed spectra, radiative transfer models have been developed. These models allow searching for optimum observation conditions and the development of algorithms to retrieve physical properties of observed objects on Earth.

Radiative transfer models that describe the relations between the physical and biochemical properties of objects and the observed radiation can be called **observation models**. In an observation model, the characteristics of the observing instrument, the observational conditions and the observable object's properties all play prominent roles. Characteristics of the instrument and the observational conditions include the viewing direction, the spectral bands, and their spectral and spatial resolutions. Object properties include canopy LAI for vegetation and suspended sediment concentration for water. In the thermal infrared, surface temperature and emissivity are important object properties. An example of another well-known physical theory in which the observation conditions play a central role is Planck's law of blackbody radiation, since it predicts the observed radiation spectrum as a function of the object's temperature.

Most observation models relevant for remote sensing applications describe scattering and absorption of radiation in various media, such as the atmosphere, water bodies, snow, plant leaves and vegetation canopies. They might also include the scanning mechanism and other observational and instrumental properties, such as the viewing direction, the spectral and spatial resolutions, and signal-to-noise levels. Models may also be coupled. This is very useful, since we have seen that most remote sensing observations involve mixtures of several media, such as the combination soil-leaf-canopy, and the combination sea bottom-water-atmosphere.

On the other hand, **process models** in earth sciences describe the evolution of geo-(bio)physical surface properties in time, independent of remote sensing observations. Examples of these process models at various time scales include numerical weather prediction models, vegetation growth models, hydrological models, oceanographic models and climate models.

Process models in geosciences usually rely on regular observations at many locations spread over a large area. Traditionally, these observations were mostly made on the ground with various instruments. Remote sensing techniques have tremendously increased the capability of spatial sampling and the consistency of measured surface parameters. However, a problem often encountered is that what can be measured by remote sensing instruments is not always the physical quantity that the geoscientist is interested in. Exceptions are the mapping of sea surface temperature, laser altimetry and gravimetry, which are of direct geophysical interest. In the majority of cases, however, there is only an indirect relationship between what is observed by the instrument and the physical object properties of interest. In these cases, the use of observation models becomes an attractive option, since these models describe the relationships between all object properties relevant to the observation and the observed remote sensing data.

In general, remote sensing observations can be related to several object properties, but also to several other influences, such as atmospheric effects. On the other hand, some surface properties may have no effect at all on these observations. These considerations lead to the following grouping of physical quantities involved in remote sensing:

1. Primary remote sensing observables, i.e. TOA (top-of-atmosphere) radiances
2. External variables that influence remote sensing observables (e.g. due to atmospheric effects, sun angle, view angle)
3. Surface properties not of interest to users but which do have an influence on remote sensing observables
4. Surface properties of interest to users which also have an influence on remote sensing observables
5. Surface properties of interest to users which have no influence on remote sensing observables.

This is summarised visually in Figure 9. For a user of remote sensing data, only quantities from category 4 are really of interest. Category 5 is also of interest to users, but undetectable by remote sensing techniques. These quantities can be measured only by other means. Categories 2 and 3 have an impact on the observations but are not of interest to users. However, it is necessary to take them into account since the observations are sensitive to them. Ignoring them might lead to wrong interpretations of the observed data.

A complete observation model describes the relations between the quantities of categories 2, 3 and 4 on the one hand, and the quantities of category 1 on the other.

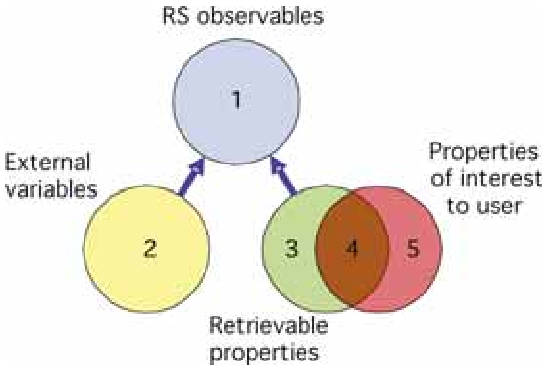


Figure 9  Earth observation variables and their meaning for users

Most radiative transfer models are not complete, as they describe only radiative transfer in particular media, such as water, soils, plant leaves, vegetation canopies or the atmosphere. Nevertheless, a complete observation model can be constructed by linking several submodels together. This is not common practice yet, but otherwise strongly recommended, since conclusions that are based on the interpretation of remote sensing data with only one submodel may not be reliable.

Finally, it should be noted that the division over the five categories is not fixed, but depends on the particular remote sensing technique. For instance, object height has no direct effect on passive remote sensing observations but it can be measured by active techniques, such as laser altimetry. Besides, which properties are of interest to the user is of course strongly discipline-dependent.

Observation models and process models can work together to enhance the quality of the interpretation of remote sensing data and fill up gaps in time when observations are not possible due to clouds or other causes. Figure 10 shows the possible interactions of observation models and process models with earth observation data, existing geographical information systems (GIS), and ground measurements, supplemented with decision support systems (DSS). A central role is played by the GIS database, which provides a common geographical reference. The diagram shows how earth observation data provide a series of snapshots of the situation at the earth surface and how this monitoring of the surface feeds a process model that is updated with actual data. The

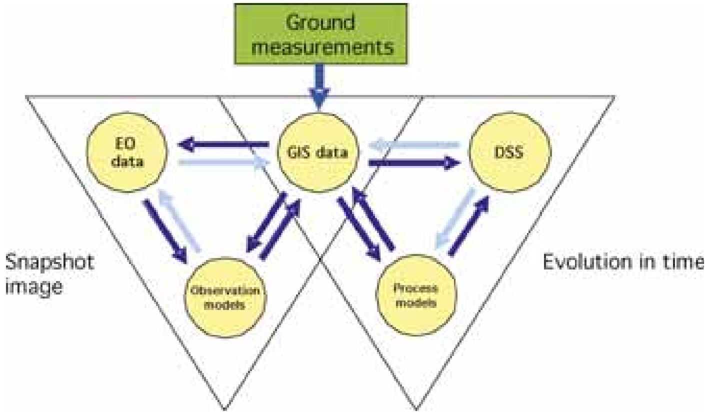


**Figure 10 Interactions between observation models and process models. Light blue arrows indicate less likely (but possible) interactions. The GIS database provides the common geographical reference**

process model provides information to the decision support system but, on the other hand, management actions could be undertaken to control the process. A good example is a water management system, where one might decide to apply irrigation if the observed vegetation appears to suffer from drought stress.

## Retrieval of surface properties

Observation models can be applied to obtain more insight into the relations between surface properties and observed earth observation data. This insight can be expressed in algorithms to derive surface properties from observations, often called retrieval. In a sense, this means using the model in the opposite direction, so one calls this model inversion. Note, however, that only very simple models have a direct inverse. For instance, the Planck function can be inverted to derive surface temperature from surface radiance (provided the emissivity is also known). Most other models are much more complex and have many more parameters, and these can only be inverted indirectly. Retrieval algorithms are based mostly on indices, combinations of remote sensing observables that are maximally sensitive to a surface property of interest and minimally sensitive to other properties. The NDVI is a well-known example. Other techniques use look-up tables or artificial neural networks. Model inversion can also be accomplished using numerical optimisation techniques, where the model is run iteratively in forward direction until its output matches the observations best, by minimising a cost function.

An issue often encountered in practice is the so-called ill-posedness of the model inversion. This means that different combinations of surface properties may produce the same set of remote sensing observables. The higher the dimensionality of the observations (number of spectral bands, linear independence), the less likely this is to happen. This problem leads to a very high sensitivity of the retrieved variables to sensor noise, so it needs to be solved. A solution is to apply a Bayesian approach (Verhoef, 2007), in which a priori information is used to regularise the retrieval algorithm. In this case, a cost function is constructed that includes not only the differences between measured and modelled observations but also those between the modelled parameters and the a priori set of parameters and their uncertainties. In this case, a weighted mean of the model solution and the *a priori* solution is found as the final outcome, and the weights are determined by the uncertainties of the a priori solution and the sensitivities to sensor noise.

Bayesian approaches have also proven to be successful in pattern recognition tasks (e.g. automatic classification of multispectral images) and in data assimilation algorithms such as Ensemble Kalman filtering. For instance, weather forecasts are often based on the operational application of these techniques. Data assimilation is often applied while a process model is being run, and when from time to time new observations become available. These new observations are then used to update the process model, taking into account uncertainties in the model and the observations. For the assimilation of earth observation data in surface process models, several approaches are possible. Some of these approaches take only a few retrieved surface parameters such as LAI as input and try to assimilate them into the process model. In an alternative approach, TOA radiances as detected by the sensor are assimilated by simulating them with a radiative transfer model, and by comparing the actual earth observation data with the simulated data. Next, in a feedback loop, the assumed surface properties are adjusted until the simulated observations match the actual observations sufficiently well. This feedback mechanism is illustrated in Figure 11.

It was assumed here that the surface properties are stored and maintained in a GIS database. Maps serve as an initial input for the GIS database, while actualised maps can be produced from the updated GIS data. This diagram illustrates the situation at one

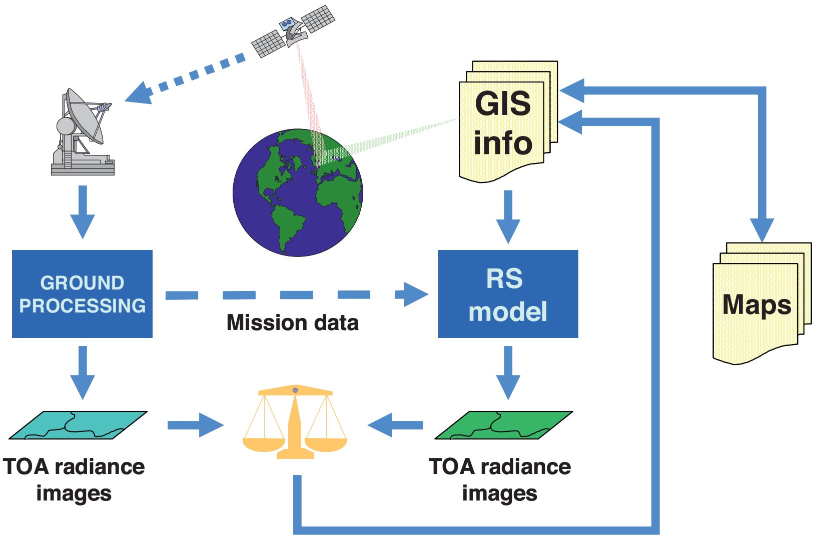


Figure 11 Feedback mechanism to match simulated and actual observations for data assimilation in a GIS database containing the surface properties

moment in time for one sensor system. However, provided the observation model (termed RS model in the diagram) is flexible, it could simulate a variety of sensors with widely different properties. In a so-called multi-sensor approach, it would be possible to assimilate remote sensing data from several different missions in a common process model. In this way, one can bridge the gaps in time of overpass of the various satellite systems, as well as gaps in sensor properties (spectral bands, resolutions, viewing directions, etc.).

Such an approach fits very well into the philosophy of the Global Earth Observation System of Systems (GEOSS), which states that (GEOSS 10-year implementation plan):

"Under GEOSS, national, regional, and international policy makers are collectively harmonizing observations, real- or near real-time monitoring, integration of information from in situ, airborne, and space-based observations through data assimilation and models."

The use of coupled radiative transfer models in a flexible generic observation model allows a line of earth observation products to be generated that is not only self-consistent, but which is also consistent with all observations, including field measurements. Coupled with process models, the quality of the retrieved surface parameters can even be further improved, since process models can constrain the model inversion to biophysically plausible solutions. Currently, most products are derived from single missions and based on several unrelated algorithms, thus increasing the chance of product inconsistencies and a greater sensitivity to sensor-specific shortcomings.

## Four-stream radiative transfer modelling

Radiative transfer models describe the propagation of radiation in a given medium on the basis of its absorption and scattering properties, and can be used to compute the reflectance and the transmittance properties of a layer, including the angular characteristics, as expressed in the bi-directional reflectance distribution function (BRDF). Such models are used in quantitative remote sensing to relate object properties to the radiation detected by a sensor, and vice versa. Four-stream models are a simplification in the sense that - internally - these models only consider isotropic diffuse upward and downward radiation, in addition to the specular radiation from the sun, and radiance in the viewing direction. During the NIWARS project (1973-1977), we used the first instance of a four-stream model. This was the model of Suits (1972) to simulate the spectral reflectance of vegetation canopies. In the early 1980s, this model was refined to improve its directional behaviour by introducing a leaf inclination distribution function. This model, called SAIL (scattering by arbitrarily inclined leaves), was published in 1984 (Verhoef, 1984) and is still widely used. Several improved variants of this model have emerged, the most sophisticated one being the SLC (soil-leaf-canopy) model, an integrated model (Verhoef & Bach, 2007) that includes a soil BRDF model, a model describing soil moisture effects, the leaf model PROSPECT (Jacquemoud & Baret, 1990), and the canopy model 4SAIL2, which has two layers to simulate leaf colour gradients and which includes crown clumping effects to simulate forests. Figure 12 illustrates the four-stream concept and the various groups of input parameters of the SLC model.

Although this four-stream modelling implies a numerical approximation, a great advantage is that the coupling with other models, such as the atmospheric radiative transfer model MODTRAN (Berk et al., 2000), is simple and straightforward. For this,

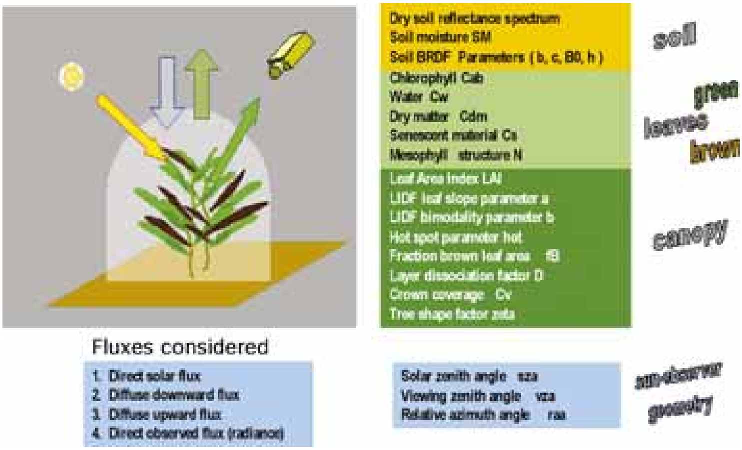


Figure 12 The four-stream concept and the parameters of the SLC model

a so-called adding algorithm is applied to couple two layers or to combine a layer with a background surface, so as to address the vertical mixing problem. If we want to simulate the observation of vegetation from space, we first run SLC and next add the atmosphere. The detailed order of working is as follows:

1. Start with the bottom canopy layer
2. Add the top canopy layer
3. Apply clumping effects to the combined canopy layer
4. Add the soil background at the bottom
5. Add the atmosphere to the canopy top.

Since only four radiation streams are involved, each of the adding steps requires very little processing power, even when working with hyperspectral data. Modelling multi-angular observations is possible by varying the viewing direction.

For heterogeneous landscapes, and with the incorporation of surface BRDF effects and adjacency effects, this chain of coupled models has been applied to simulate the SPECTRA mission, and is still being used to support the interpretation of multi-angular CHRIS-PROBA data. In an ESA project simulating the SPECTRA mission and with the help of SLC, it was demonstrated for a boreal forest region in Finland (Sodankylä) how by means of this sensor maps of fAPAR and the surface albedo could be produced

(Figure 13). Here, these quantities were not estimated from dedicated retrieval algorithms, but computed directly from the radiative transfer model that was run at 10 nm steps.

Summarising, we can state that coupled radiative transfer modelling has many applications in the fields of education (giving more insight and a better understanding), mission performance analysis and the development of retrieval algorithms. For vegetation monitoring, we can think of the retrieval of LAI, fCover, fAPAR, albedo, etc.; fluorescence modelling; thermal applications; energy balance; crop growth monitoring; and data assimilation in growth models. For water quality mapping, a better correction for atmospheric effects can be expected, as well as improved algorithms for the retrieval of chlorophyll, sediment and other substances. This now brings me to a closer look at the future.

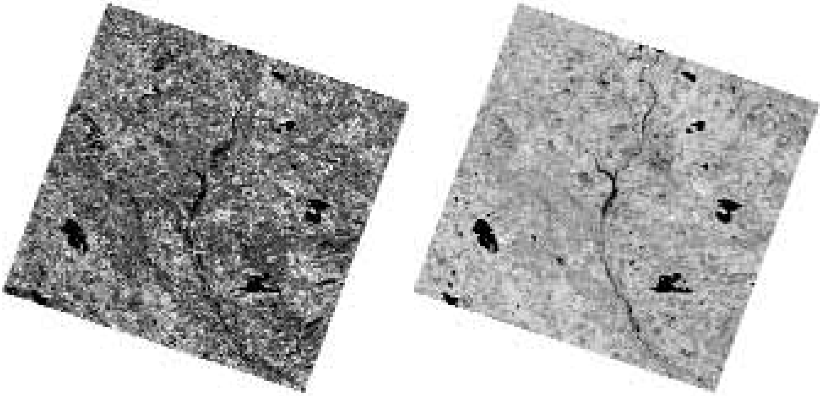

**Figure 13 Maps of fAPAR (left) and surface albedo (right) derived from simulated SPECTRA data using the model SLC coupled with MODTRAN. Each image measures 1000 x 1000 pixels at 50 m ground sampling distance.**

## The future

The prime mission of ITC comprises education and capacity building for developing countries. Developing countries have their own specific problems, but the need for accurate, reliable and up-to-date geo-information on water and land areas is universal. Water quality, food production, biodiversity and climate change are global issues, and the retrieval of surface properties from earth observation data in developing countries is as important as anywhere else.

Looking into the future, I think that there are many important things left to be done, and I am convinced that the inspiring environment at ITC, with its high concentration of geoscience and remote sensing experts, will stimulate us to propagate the application of quantitative and physically-based methods in remote sensing research and education.

I am looking forward to discussing and working with colleagues and PhD students on a stronger integration of remote sensing and GIS technologies, on the integration of observation models with process models, on the application of multi-sensor approaches, and on the definition of more reliable and consistent output products. In all these areas, we will initiate new PhD projects and try to participate in contract research projects.

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Just last week, I got my appointment as a full-time professor serving both the Water Resources and Natural Resources departments. I thank the members of the Supervisory Board and the Scientific Council for their confidence, and I am very grateful that they have enabled me to contribute to the research and education at ITC, in both water and land applications.

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For the first four years of my career, from 1973 to 1977, I was engaged in the NIWARS project under the leadership of Nico Bunnik. After this, Nico and I started working in remote sensing at the National Aerospace Laboratory (NLR) in Amsterdam. At NLR, I had the opportunity to learn a lot about mathematical physics, image processing and numerical modelling. I am grateful to NLR for supporting my development in a scientific direction. I thank many colleagues at NLR, first in Amsterdam, and since 1987 in "the polder". In particular, I would like to mention some colleagues of the geomatics group, the so-called "geo-mates", such as Hein Noorbergen, Rob van Swol and Gert van der Burg.

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Since 1996, I have been involved in a long series of ESA projects, mostly to study future mission concepts such as the SPECTRA mission and the vegetation fluorescence mission FLEX. I would like to thank my colleagues at ESTEC, in particular Mike Rast and Michael Berger (now at ESRIN in Italy), and the many international co-investigators from various companies and universities I have enjoyed working with in many interesting projects, for instance Massimo Menenti, Heike Bach, John Miller, Fred Baret, Stephane Jacquemoud, Luis Guanter, José Moreno, and many others.

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Mr Rector, members of the Scientific Council, the Supervisory Board, ladies and gentlemen, thank you very much for your attention. I have spoken.

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